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Behavioral Intention to Use Ai-Enabled Bim in Malaysia – An Extended Utaut-1 Model

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ABSTRACT

The integration of artificial intelligence (AI) with Building Information Modeling (BIM) has strong potential to transform the construction industry, yet adoption remains limited, especially in developing contexts. This study investigates the factors influencing behavioral intention to use AI-enabled BIM systems in Malaysia's construction sector by extending the UTAUT-1 framework with initial trust and individual difference variables. A quantitative research design was used, based on survey data collected from G7 construction firms. The proposed model examined performance expectancy, effort expectancy, social influence, self-efficacy, personal innovativeness, and initial trust and assessed the mediating role of trust. Structural equation modeling was applied to test the hypothesized relationships. The findings show that performance expectancy, effort expectancy, social influence, and initial trust significantly influence behavioral intention, with effort expectancy emerging as the strongest predictor. By contrast, self-efficacy and personal innovativeness do not have significant direct effects. Initial trust also partially mediates the relationships between performance expectancy, social influence, and self-efficacy with behavioral intention, but not those involving effort expectancy or personal innovativeness. However, even though self-efficacy does not have a significant direct effect on behavioral intention, it has a meaningful indirect effect through initial trust, indicating that confidence in one's abilities helps build trust in AI-enabled BIM systems. The study contributes to theory by integrating UTAUT-1, trust theory, and individual difference perspectives, while also challenging the view that trust always mediates adoption relationships. Practically, the findings highlight the importance of system usability, performance benefits, organizational support, and trust-building measures. Overall, the study deepens understanding of technology adoption in AI-driven construction environments and provides a useful basis for future research and industry implementation.

Keywords: AI, Building Information Modeling, Self-Efficacy, Personal Innovativeness, Initial Trust, UTAUT-1

INTRODUCTION

The global construction industry is at a critical point, facing increasing work complexity, project fragmentation, dynamic operations, reliance on human input, strict budget constraints, and the need to boost productivity (Datta et al., 2024; Dagou et al., 2024; Egwim et al., 2023; Lee et al., 2022; Nnaji et al., 2023; Rahim et al., 2023; Seyman-Güray, 2023). In response, the sector is undergoing a significant digital shift, moving away from traditional, often isolated, paper-based processes toward integrated, data-driven approaches (Datta et al., 2024; Srivastava et al., 2022). Leading this change is Building Information Modeling (BIM), a transformative technology that goes beyond simple 3D modeling. BIM is a comprehensive process that creates and manages all information about a built asset throughout its lifecycle—from planning and design to construction and operation—encouraging greater collaboration and transparency among stakeholders, such as architects, engineers, manufacturers, and others (Alavi et al., 2024; Datta et al., 2024; Egwim et al., 2023; Zawada et al., 2024).

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The recent integration of BIM with Artificial Intelligence (AI) has led to a variety of AI-enabled BIM systems. These systems enhance traditional BIM features by integrating machine learning, natural language processing, and predictive analytics (Ghimire et al., 2024; Pan & Zhang, 2023). This combination enables advanced applications such as generative design (automatically producing optimal design options), automated clash detection and code compliance checking, predictive risk and safety management, and real-time progress monitoring via computer vision (Waqar et al., 2023; Zawada et al., 2024). This development signifies a shift from a descriptive digital model to a prescriptive and intelligent digital partner.

In Malaysia, the construction sector contributes significantly to socio-economic development and to the country's GDP (Rahim et al., 2023). Recognizing the importance of technological modernization, Malaysian authorities have implemented key policies. The Construction Industry Development Board (CIDB) introduced the Construction 4.0 Strategic Plan (2021-2025), which explicitly requires the use of BIM for all public projects valued at RM100 million and above (Construction Industry Development Board, 2021). This top-down approach is supported by efforts to build a digitally skilled workforce and raise awareness of advanced construction technologies. Meanwhile, advances in artificial intelligence (AI) offer new opportunities to integrate machine learning, predictive analytics, and automation into traditional BIM workflows. Only large firms—especially those registered with the CIDB as Grade 7 (G7)—have the capital, scale, and infrastructure necessary to adopt AI-enabled BIM systems (Malik et al. 2022).

However, despite these commendable efforts, the industry's path toward full digital maturity, including AI-enabled tools such as AI-enabled BIM, is still slow and faces significant challenges (Adebayo et al., 2025; Pan & Zhang, 2023; Robin & Yahya, 2023). As of 30 November 2025, only seven government construction projects listed on CIDB's website have been completed using the BIM system (CIDB, November 30, 2025). The implementation of BIM in Malaysia continues to evolve (Musarat et al., 2023; Omar et al., 2022; Waqar et al., 2023; Yizing et al., 2025). The adoption of more advanced AI-enabled BIM systems is in its early stages (Pan & Zhang, 2023) and is hampered by a complex mix of technological, organizational, social, and human factors, as perceived by construction professionals (Adebayo et al., 2025).

Therefore, a few significant gaps exist, which are contextual, empirical, and theoretical, that lead to the following research objectives. The main objective of this study is to evaluate the relationships between performance expectancy (PE), effort expectancy (EE), social influence (SI), self-efficacy (SE), personal innovativeness (PI), and initial trust (IT) and their direct and indirect effect on behavioral intention (BI) regarding the use of AI-enabled BIM systems among G7 construction firms in Malaysia, using an extended UTAUT-1 conceptual model. More specifically, this study will: (1) examine the effect of performance expectancy (PE), effort expectancy (EE), social influence (SI), self-efficacy (SE), personal innovativeness (PI), and initial trust (IT) on behavioral intention (BI) to use AI-enabled BIM systems among G7 construction firms in Malaysia. (2) Assess whether initial trust mediates the relationship between the determinants and behavioral intention. (3) Determine the most important factors influencing AI-enabled BIM adoption among Malaysian construction professionals. (4) Provide practical recommendations for construction firms, policymakers, and software developers.

LITERATURE REVIEW

Underpinning Theory

Although the Technology Acceptance Model (TAM) has been widely applied in construction management research, its emphasis on perceived usefulness and perceived ease of use may not adequately explain users' acceptance of emerging technologies characterized by autonomy, uncertainty, and intelligent decision-making, such as AI-enabled Building Information Modeling (AI-enabled BIM). AI-enabled BIM extends beyond conventional information systems by incorporating predictive analytics, machine learning, and automated decision support, thereby introducing additional cognitive and psychological considerations that are not fully captured by TAM.

Accordingly, this study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT-1) (Venkatesh et al., 2003) as its primary theoretical foundation. Compared with TAM, UTAUT-1 provides a more comprehensive explanation of technology acceptance by incorporating cognitive determinants (performance expectancy and effort expectancy), social determinants (social influence), and organizational factors (facilitating conditions). Nevertheless, recent studies have suggested that UTAUT-1 should be extended with context-specific constructs when investigating emerging technologies in specialized domains (Venkatesh, 2020; Nnaji et al., 2023). Such extensions improve the model's explanatory capability by accounting for characteristics unique to the technology and its application environment.

Following these recommendations, this study extends UTAUT-1 by incorporating three domain-specific constructs. Self-efficacy, derived from Social Cognitive Theory (Bandura, 1986), reflects users' confidence in their capability to learn and effectively operate AI-enabled BIM systems. Personal innovativeness, grounded in the Diffusion of Innovation theory (Rogers, 2003) and operationalized by Agarwal and Prasad (1998), captures individuals' willingness to experiment with new technologies. Initial trust, based on McKnight's trust theory (McKnight, 2005), is positioned as a key psychological mechanism that influences users' willingness to rely on intelligent systems whose operations may not be fully transparent.

Integrating these constructs addresses an important theoretical gap in the AI-enabled BIM literature. While previous studies have primarily examined technological and organizational determinants of BIM adoption, considerably less attention has been devoted to individual psychological characteristics and trust formation during the early stages of AI-enabled BIM adoption, particularly in developing countries. Consequently, this study proposes an extended UTAUT-1 model that integrates cognitive, social, and psychological perspectives to provide a more comprehensive explanation of employees' behavioral intention to adopt AI-enabled BIM systems within Malaysia's construction industry.

Hypotheses Development

The Unified Theory of Acceptance and Use of Technology (UTAUT-1) (Venkatesh et al., 2003) provides the conceptual basis for examining the determinants of behavioral intention to adopt AI-enabled BIM systems. Since this study investigates behavioral intention rather than actual system use, facilitating conditions are excluded because they primarily predict usage behavior after adoption. Likewise, the four original UTAUT-1 moderators (age, gender, experience, and voluntariness of use) are not incorporated, as the objective is to examine the direct determinants of behavioral intention rather than differences across demographic groups.

Performance Expectancy (PE)

Performance expectancy refers to the degree to which an individual believes that using AI-enabled BIM systems will improve job performance and task accomplishment (Venkatesh et al., 2003; Rana et al., 2024; Heo & Na, 2025). Within construction projects, AI-enabled BIM has the potential to improve design accuracy, automate repetitive tasks, enhance project coordination, optimize resource allocation, and support faster decision-making. Employees who perceive these performance benefits are therefore more likely to develop favorable intentions toward adopting the technology.

This relationship has been consistently supported across various technological contexts, including artificial intelligence, construction technologies, ChatGPT, smart cities, Islamic fintech, online insurance, e-learning, microlearning, and AI-assisted learning (Abbad, 2021; Alvi, 2021; Handa & Kaur, 2025; Heo & Na, 2025; Lee et al., 2024; Rahim et al., 2023; Rana et al., 2024; Tai et al., 2025; Tuyen & Nguyen, 2025; Wu et al., 2022, 2025). Accordingly, it can be hypothesized that:

H1: Performance expectancy positively influences behavioral intention to adopt AI-enabled BIM systems.

Effort Expectancy (EE)

Effort expectancy refers to the degree to which users perceive AI-enabled BIM systems as easy to learn and operate (Venkatesh et al., 2003; Tai et al., 2025; Wu et al., 2025). AI-enabled BIM applications often introduce

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sophisticated functionalities that may increase users' perceived complexity. Consequently, technologies that require less effort to understand and use are more likely to encourage acceptance.

Numerous empirical studies have reported a positive association between effort expectancy and behavioural intention across AI, BIM, ChatGPT, Internet of Things, e-health, smart cities, generative AI, and educational technologies (Abbad, 2021; Arfi et al., 2021; Heo & Na, 2025; Kim et al., 2024; Lee et al., 2024; Rana et al., 2024; Wu et al., 2025; Yizing et al., 2025). Therefore, it can be hypothesized that:

H2: Effort expectancy positively influences behavioral intention to adopt AI-enabled BIM systems.

Social Influence (SI)

Social influence is the extent to which individuals perceive that important others believe they should use AI-enabled BIM systems (Venkatesh et al., 2003; Heo & Na, 2025). In construction organizations, management support, peer encouragement, professional norms, and client expectations may shape employees' willingness to adopt new technologies. These influences are especially important in the early stages of AI adoption, when users face uncertainty about the technology.

Empirical evidence consistently demonstrates that social influence positively affects behavioral intention across AI, BIM, IoT, ChatGPT, online insurance, and smart city technologies (Arfi et al., 2021; Heo & Na, 2025; Kim et al., 2024; Lee et al., 2024; Rana et al., 2024; Wu et al., 2025; Yizing et al., 2025). Therefore, it can be hypothesized that:

H3: Social influence positively influences behavioral intention to adopt AI-enabled BIM systems.

Self-Efficacy (SE)

Drawing upon Social Cognitive Theory (Bandura, 1986), self-efficacy reflects individuals' confidence in their ability to successfully learn and use AI-enabled BIM systems. Users with higher self-efficacy are generally more willing to explore unfamiliar technologies, overcome implementation challenges, and persist despite initial difficulties. Consequently, self-efficacy is expected to strengthen behavioral intention toward AI-enabled BIM adoption.

Previous studies involving AI-based healthcare, facial recognition, ChatGPT, and AI-supported learning consistently demonstrate that self-efficacy positively influences behavioral intention (David-Negre & Gutiérrez-Taño, 2025; Kwak et al., 2022; Ramos Salazar & Peeples, 2025; Shahzad et al., 2025; Sumandal, 2023; Wang, Ruan, et al., 2024). Therefore, it can be hypothesized that:

H4: Self-efficacy positively influences behavioral intention to adopt AI-enabled BIM systems.

Personal Innovativeness (PI)

Personal innovativeness refers to an individual's willingness to experiment with and embrace new information technologies (Agarwal & Prasad, 1998; Rogers, 2003). Individuals with higher personal innovativeness are generally more receptive to emerging technologies, perceive lower uncertainty, and demonstrate greater willingness to adopt AI-enabled BIM despite its novelty and complexity.

Prior research has established significant relationships between personal innovativeness and behavioral intention across AI-based medical diagnosis, AI voice assistants, Internet of Things, social media technologies, and ChatGPT (Aldahdouh et al., 2020; Fan et al., 2020; Gokcearslan et al., 2024; Lee et al., 2021; Ramos Salazar & Peeples, 2025). Therefore, it can be hypothesized that:

H5: Personal innovativeness positively influences behavioral intention to adopt AI-enabled BIM systems.

Initial Trust (IT) as a Predictor of Behavioral Intention

AI-enabled BIM systems frequently perform autonomous analyses and generate recommendations through complex algorithms that are not fully transparent to end users. Under such conditions, users often rely on trust when deciding whether to accept and use the technology. Based on McKnight's trust theory (McKnight, 2005), initial trust represents users' willingness to rely on a technology despite limited prior experience. It reflects beliefs regarding the system's competence, reliability, integrity, and ability to act in users' best interests (McKnight et al., 2011; Rousseau et al., 1998).

Although trust has been widely recognized as a critical determinant of AI adoption, its role remains insufficiently explored within AI-enabled BIM research, particularly as a mechanism linking users' perceptions to behavioral intention. Existing evidence from AI healthcare, autonomous vehicles, smart cities, e-health, generative AI, and facial recognition consistently indicates that higher levels of initial trust lead to stronger behavioral intentions (Al-Haraizah et al., 2025; Arfi et al., 2021; Chan & Lee, 2021; Kim, Choi, & Fotso, 2024; Masrek et al., 2025; Su et al., 2025; Yu et al., 2024). Therefore, it can be hypothesized that:

H6: Initial trust positively influences behavioral intention to adopt AI-enabled BIM systems.

Initial Trust as a Mediator

The increasing autonomy and complexity of AI-enabled BIM systems introduce uncertainty regarding the accuracy, transparency, and reliability of AI-generated recommendations. Unlike conventional BIM applications, AI-enabled BIM performs predictive analyses and automated decision support, often through algorithms whose internal processes are not fully understood by users. Under such conditions, initial trust becomes a critical psychological mechanism that influences whether construction professionals are willing to rely on and adopt the technology. McKnight's trust theory (McKnight, 2005) posits that when users have limited prior experience with a technology, their behavioral decisions are primarily shaped by initial trust, which reflects beliefs about the system's competence, reliability, integrity, and dependability (McKnight et al., 2011). Consequently, initial trust provides the psychological foundation through which users convert favorable perceptions of AI-enabled BIM into behavioral intention.

Previous studies consistently demonstrate that trust functions as an important mediating mechanism in the adoption of emerging digital technologies. For example, Cheng et al. (2022) found that trust mediated the relationships between performance expectancy, effort expectancy, and healthcare professionals' intention to use AI-assisted diagnosis systems. Similarly, Dai et al. (2025) reported that trust mediated the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on nurses' behavioral intention to adopt medical AI. Studies involving generative AI and ChatGPT have likewise shown that trust transmits the effects of users' perceptions and individual characteristics on technology usage (Ali et al., 2023; Shahzad et al., 2025; Xu et al., 2024). Collectively, these findings suggest that users' positive evaluations of an AI system do not directly translate into adoption intentions unless sufficient trust has first been established.

The development of initial trust is influenced by both technology-related perceptions and individual characteristics. From the UTAUT-1 perspective, users who perceive AI-enabled BIM as useful (performance expectancy), easy to use (effort expectancy), and socially endorsed (social influence) are more likely to develop trust in the technology. Empirical support for these relationships has been reported across AI, autonomous vehicles, healthcare, and educational technologies (Amin et al., 2025; Chan & Lee, 2021; Cheng et al., 2022; Dai et al., 2025; Fan et al., 2020). Beyond these cognitive and social determinants, individual differences also contribute to trust formation. Users with higher self-efficacy tend to feel more capable of interacting with AI-enabled BIM systems and are therefore less likely to perceive uncertainty, whereas individuals with greater personal innovativeness are generally more willing to explore unfamiliar technologies and develop trust in their capabilities. These relationships have been supported in studies involving facial recognition systems, generative AI, fintech, AI-enabled services, and mobile applications (David-Negre & Gutiérrez-Taño, 2025; Kurniawati & Wijayadne, 2026; Novianti et al., 2025; Salih et al., 2025; Shahzad et al., 2025; Wijayadne, 2025).

Accordingly, this study proposes that performance expectancy, effort expectancy, social influence, self-efficacy, and personal innovativeness positively influence initial trust in AI-enabled BIM systems.

H7: Performance expectancy positively influences initial trust.

H8: Effort expectancy positively influences initial trust.

H9: Social influence positively influences initial trust.

H10: Self-efficacy positively influences initial trust.

H11: Personal innovativeness positively influences initial trust.

Building upon these relationships, this study further proposes that initial trust serves as the psychological mechanism through which cognitive, social, and individual factors influence behavioral intention. When users perceive AI-enabled BIM systems to be beneficial, easy to use, socially supported, and compatible with their abilities and innovative tendencies, these favorable perceptions strengthen their trust in the technology. In turn, higher initial trust increases their willingness to adopt AI-enabled BIM systems. Previous studies consistently support the mediating role of trust across various AI contexts, including service robots, autonomous vehicles, healthcare AI, generative AI, facial recognition systems, and ChatGPT (Amin et al., 2025; Chan & Lee, 2021; David-Negre & Gutiérrez-Taño, 2025; Lin & Lee, 2025; Shahzad et al., 2025; Yu et al., 2024). Therefore, the following mediation hypotheses are proposed:

H6a: Initial trust mediates the relationship between performance expectancy and behavioral intention.

H6b: Initial trust mediates the relationship between effort expectancy and behavioral intention.

H6c: Initial trust mediates the relationship between social influence and behavioral intention.

H6d: Initial trust mediates the relationship between self-efficacy and behavioral intention.

H6e: Initial trust mediates the relationship between personal innovativeness and behavioral intention.

The Research Model

Therefore, Figure 1 presents the conceptual framework of this study. Building upon the Unified Theory of Acceptance and Use of Technology (UTAUT-1), the model proposes that performance expectancy (PE), effort expectancy (EE), social influence (SI), self-efficacy (SE), and personal innovativeness (PI) directly influence employees' behavioral intention (BI) to adopt AI-enabled BIM systems. In addition, initial trust (IT) is positioned as a mediating construct that explains how these cognitive, social, and individual factors translate into behavioral intention. By integrating self-efficacy from Social Cognitive Theory (Bandura, 1986), personal innovativeness from Diffusion of Innovation Theory (Rogers, 2003; Agarwal & Prasad, 1998), and initial trust from McKnight's Trust Theory (McKnight, 2005), the proposed model extends UTAUT-1 to better capture the psychological processes underlying AI-enabled BIM adoption. Consequently, the extended framework is expected to provide greater explanatory and predictive power than the original UTAUT-1 in explaining employees' behavioral intention to adopt AI-enabled BIM systems within Malaysia's construction industry.

THE RESEARCH METHODOLOGY

This study employed a quantitative research approach to investigate the determinants of employees' behavioral intention to adopt Artificial Intelligence-enabled Building Information Modeling (AI-enabled BIM) systems within Malaysia's construction industry. A quantitative approach was considered appropriate because the study sought to empirically test theoretically derived hypotheses and examine the relationships among multiple latent constructs using statistical modeling.

A cross-sectional survey design was adopted to collect data from respondents at a single point in time. This design is widely used in technology adoption research because it enables researchers to examine behavioral perceptions and intentions efficiently across a large population while providing sufficient statistical power for

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structural equation modeling. The target population comprised technical and managerial professionals employed in Malaysian CIDB Grade G7 construction firms, including engineers, project managers, BIM managers and coordinators, architects, quantity surveyors, site supervisors, and other professionals directly involved in BIM implementation or digital construction activities. G7 contractors were selected because they represent the largest and most technologically capable construction organizations in Malaysia and are therefore the most likely adopters of AI-enabled BIM technologies.

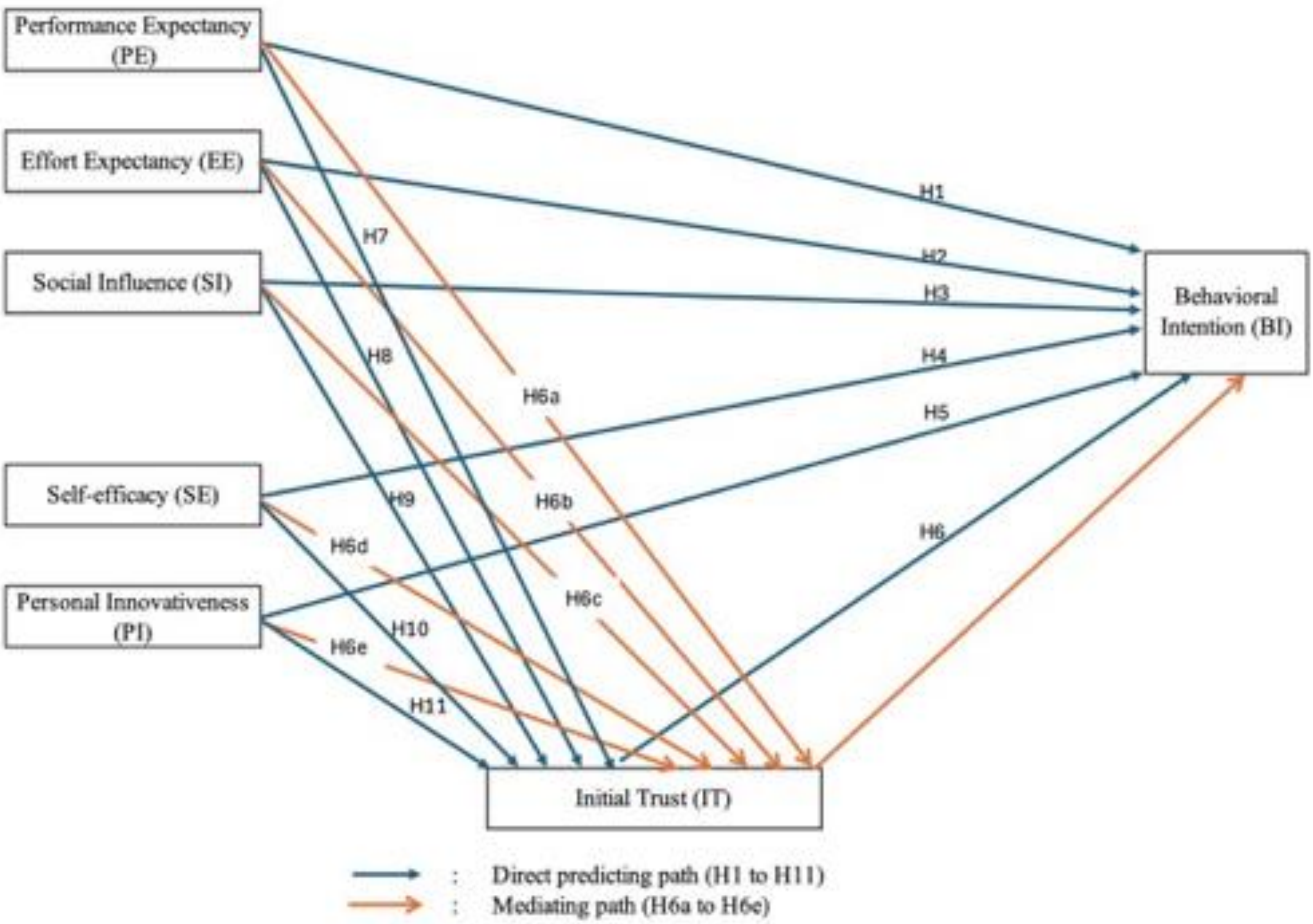

Figure 1: Research Model

Data were collected using a structured, self-administered questionnaire developed from previously validated measurement scales reported in the technology adoption and information systems literature. The questionnaire consisted of three sections. The first section collected respondents' demographic and professional information, including gender, age, educational qualification, job position, years of industry experience, BIM experience, and AI usage experience. The second section measured the independent constructs of performance expectancy, effort expectancy, social influence, self-efficacy, and personal innovativeness, together with the mediating construct of initial trust. The third section measured behavioral intention to adopt AI-enabled BIM systems. All measurement items were adapted to suit the AI-enabled BIM context while preserving their original conceptual meanings. Responses were recorded using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), which is widely accepted for measuring behavioral perceptions because it provides adequate response variability while remaining easy for respondents to understand.

To enhance the representativeness and generalizability of the findings, this study employed a probability sampling approach in which every eligible member of the target population had a known probability of selection. Following data collection, the dataset underwent a rigorous screening process to ensure data quality prior to statistical analysis. Missing values, response completeness, and potential multivariate outliers were examined, with multivariate outliers identified using Mahalanobis distance. Cases exhibiting excessive multivariate

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deviation were removed to improve the robustness of the statistical estimates. The remaining responses constituted the final dataset used for subsequent analyses.

The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented in SmartPLS 4. PLS-SEM was selected because it is particularly suitable for analyzing complex research models involving multiple latent constructs, simultaneous direct and indirect relationships, and prediction-oriented research objectives. Furthermore, PLS-SEM does not require multivariate normality and performs well when analyzing behavioral research models that incorporate mediation effects.

The analysis followed the recommended two-stage PLS-SEM procedure comprising measurement model assessment followed by structural model assessment. The measurement (outer) model was first evaluated to establish the reliability and validity of the measurement instruments. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR), while convergent validity was evaluated through indicator loadings and average variance extracted (AVE). Discriminant validity was assessed using cross-loadings, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT). To minimize potential estimation bias, multicollinearity was examined using variance inflation factor (VIF) values, while common method bias was assessed using the full collinearity approach.

Following confirmation of an acceptable measurement model, the structural (inner) model was evaluated to examine the hypothesized relationships among the constructs. The model's explanatory power was assessed using the coefficient of determination (R^2), while effect sizes (f^2) were examined to determine the relative contribution of each predictor. Predictive relevance was evaluated using Stone-Geisser's Q^2 statistic to assess the model's out-of-sample predictive capability. In addition, Importance-Performance Map Analysis (IPMA) was conducted to identify constructs that not only exert substantial influence on behavioral intention but also offer the greatest potential for managerial improvement. Statistical significance of the direct and indirect (mediating) relationships was determined using the non-parametric bootstrapping procedure with bias-corrected confidence intervals, following established recommendations for mediation analysis in PLS-SEM.

Overall, the adopted methodology provides a rigorous and systematic empirical framework for examining the determinants of AI-enabled BIM adoption among Malaysian construction professionals. By integrating established measurement procedures with advanced PLS-SEM techniques, the study ensures the reliability, validity, and predictive capability of the proposed model while generating robust empirical evidence on the cognitive, social, and psychological factors that shape employees' behavioral intention to adopt AI-enabled BIM systems in Malaysia's construction industry.

CONCLUSION

Given the limited research on behavioral intention to adopt AI-enabled BIM systems, the primary goal of this study is to examine how the identified variables influence this intention. In this study, sixteen hypotheses, eleven on direct effects and five on mediating effects, were developed. The findings reveal that performance expectancy (PE), effort expectancy (EE), social influence (SI), and initial trust (IT) significantly affect behavioral intention (BI), whereas self-efficacy and personal innovativeness do not have a direct, significant effect on BI. Among these, effort expectancy and performance expectancy are the strongest predictors, indicating that users value ease of use and perceived usefulness when adopting AI-enabled BIM. Furthermore, all five constructs (PE, EE, SI, SE, PI) significantly influence initial trust, with self-efficacy the most influential. This suggests that users' confidence in their ability to use the system plays a crucial role in trust formation. The mediation analysis reveals that initial trust partially mediates the relationships between certain predictors and behavioral intention, particularly for performance expectancy, social influence, and self-efficacy. However, no mediation effect was found for effort expectancy and personal innovativeness. Overall, the findings suggest that AI-enabled BIM adoption is primarily driven by functional factors (usefulness and ease of use), with social influence and trust providing support, while individual traits play a secondary role.

The study makes several important theoretical contributions. First, it extends technology adoption research by conceptualizing AI-enabled BIM as an integrated intelligent technology rather than examining AI and BIM separately. Second, it demonstrates that UTAUT-1 provides a stronger theoretical foundation than the Technology Acceptance Model (TAM) for explaining adoption of complex AI-driven technologies in construction. Third, the findings challenge the conventional assumption that individual characteristics such as self-efficacy and personal innovativeness always exert direct influences on behavioral intention. Instead, self-efficacy contributes indirectly through initial trust, while personal innovativeness shows limited influence within structured organizational environments. Finally, the study advances trust theory by demonstrating that initial trust selectively mediates the effects of performance expectancy, social influence, and self-efficacy, but not effort expectancy and personal innovativeness. This highlights trust as a context-dependent psychological mechanism rather than a universal mediator and contributes to a more nuanced understanding of technology adoption in AI-driven environments.

From a practical perspective, the findings provide actionable guidance for construction firms, policymakers, and technology developers. Construction organizations should prioritize improving system usability, demonstrating measurable performance benefits, strengthening organizational support, and providing continuous user training to enhance self-efficacy and trust. Policymakers can accelerate AI-enabled BIM adoption through national standards, financial incentives, professional training programs, and educational initiatives that strengthen digital competencies within the construction workforce. Technology developers should focus on developing user-friendly, transparent, reliable, and explainable AI-enabled BIM systems while offering comprehensive technical support and training to reduce user uncertainty. The Importance–Performance Map Analysis further indicates that improving effort expectancy and performance expectancy should receive the highest priority because these factors combine high importance with moderate current performance. Collectively, the findings demonstrate that successful AI-enabled BIM implementation requires coordinated efforts among organizations, policymakers, and technology providers to improve usability, performance, trust, and organizational readiness.

Limitations And Future Research

Although this study makes significant theoretical and practical contributions, several limitations provide opportunities for future research. First, the study focuses exclusively on Malaysian CIDB G7 construction firms. As these organizations are generally larger, more resource-rich, and technologically advanced than smaller contractors, the findings may not be fully generalizable to small and medium-sized enterprises or construction industries in other countries. Future studies should validate the proposed model across different organizational sizes, industrial sectors, and national contexts to strengthen its external validity.

Second, the study employed a cross-sectional survey design, capturing respondents' perceptions at a single point in time. Because technology adoption is dynamic, users' perceptions of usefulness, effort, and trust may evolve as they gain practical experience with AI-enabled BIM. Longitudinal studies are therefore recommended to investigate how these perceptions change over time and how behavioral intention develops into actual system usage and continued adoption.

Third, the research relied on self-reported questionnaire data. Although statistical tests indicated that common method bias was not a significant concern, responses may still be influenced by social desirability, respondent subjectivity, or organizational expectations. Future studies should incorporate multiple data sources, such as system usage records, project performance indicators, managerial assessments, and qualitative interviews, to triangulate findings and provide a richer understanding of AI-enabled BIM implementation. In addition, future research should move beyond behavioral intention to investigate actual technology usage, implementation success, and project outcomes.

Finally, the proposed model does not explicitly incorporate contextual or environmental variables, such as organizational culture, leadership support, regulatory frameworks, technological maturity, project complexity, or technological infrastructure, which may influence technology adoption. Future research should investigate these moderating variables to provide a more context-sensitive explanation of AI-enabled BIM adoption. Researchers should also extend the model by incorporating AI-specific constructs, including algorithmic transparency, explainability, perceived autonomy, ethical concerns, and data privacy, which are becoming increasingly important as AI technologies become more sophisticated. Multi-level research examining interactions among individual, project, organizational, and institutional factors would provide a more comprehensive understanding of technology adoption. Overall, future studies should adopt broader, longitudinal, mixed-method, and AI-specific approaches to advance knowledge on the adoption and implementation of AI-enabled BIM within the construction industry.

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Author contributions

Shiau-Yoon Choong conceptualized the whole research. Zahir Osman supervised and reviewed the research.

Ethical approval

Ethics approval has been obtained from the first author’s institution.

Competing interests

The authors declare that they have no competing interests.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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